Performance Comparison of Starting Speed Control of Induction Motor

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Abstract

In the induction motor speed control without sensors operated by the method Field Oriented Control (FOC) was required an observer to estimate the speed. Obsever methods have been developed, among others, was the method of Self-Constructing Fuzzy Neural Network (SCFNN) with some training algorithms such as backpropagasi (BP). Levenberg Marquard (LM) etc.. In the induction motor control techniques were also developed methods of Direct Torque Control (DTC) with observer Recurrent Neural Network (RNN). This paper compares the performance of the motor response to initial rotation between SCFNN observer method that uses the LM training algorithm with DTC control technique with RNN observer. From the observation performance of the motor response to initial rotation of the two methods shows that the LM method has better performances than the RNN. This can be seen on both the parameters : overshoot, rise time, settling time, peak and peak time. With the right method, can enhance better performance of the system. With the improvement of system performance, is expected to increase work efficiency in the industrial world, so overall, particularly for systems that require high precision, FNN methodcan be said to be better.

Keywords*: Motor Speed control without sensors, FOC, SCFNNO, DTC, Levenberg Marquardt and RNN*

1. Introduction

DC motors are the most ideal type of motor for electric control because of its speed can be adjusted easily and does not require a converter. The weakness of DC motors are relatively expensive, relatively large size, there is the commutator and brushes in the motor, thus requiring the complex maintenance and should be done routinely. The stoping of operation during maintenance, certainly is not desired in the industry, because it will disrupt the process and reduce yield (production) industry, which affects to the company's losses. [9]

BLDC motors have many advantages over brushed DC motors and induction motors, such as a better speed *versus* torque characteristics, high dynamic response, high efficiency and reliability, long operating life (no brush erosion), noiseless operation, higher speed ranges, and reduction of electromagnetic interference (EMI). In addition, the ratio of delivered torque to the size of the motor is higher, making it useful in applications where space and weight are critical factors, especially in aerospace applications. The control of BLDC motors can be done in sensor or sensorless mode, but to reduce overall cost of actuating devices, sensorless control techniques are normally used. The advantage of sensorless BLDC motor control is that the sensing part can be omitted, and thus overall costs can be considerably reduced. The disadvantages of sensorless control are higher requirements for control algorithms and more complicated electronics [10]. All of the electrical motors that do not require an electrical connection (made with brushes) between stationary and rotating parts can be considered as brushless permanent magnet (PM) machines [11], which can be categorised based on the PMs mounting and the back-EMF shape. The PMs can be *surface mounted on the rotor* (SMPM) or installed *inside of the rotor* (IPM) [12], and the back-EMF shape can either be sinusoidal or trapezoidal. According to the back-EMF shape, *PM AC synchronous motors* (PMAC or PMSM) have sinusoidal back-EMF and *Brushless DC motors* (BLDC or BPM) have trapezoidal back-EMF. A PMAC motor is typically excited by a three-phase sinusoidal current, and a BLDC motor is usually powered by a set of currents having a quasi-square waveform [13,14]. Because of their high power density, reliability, efficiency, maintenance free nature and silent operation, permanent magnet (PM) motors have been widely used in a variety of applications in industrial automation, computers, aerospace, military (gun turrets drives for combat vehicles) [10], automotive (hybrid vehicles) [15] and household products. However, the PM BLDC motors are inherently electronically controlled and require rotor position information for proper commutation of currents in its stator windings. It is not desirable to use the *position sensors* for applications where reliability is of utmost importance because a sensor failure may cause instability in the control system.

In the speed regulation system of the induction motor that be operated by FOC method required a speed sensor to observe the value of the speed. The observation of speed sensor of induction motor is compared to the speed setpoint, which is then fed to the controller to control the speed to match the setpoint at the input. Usually the location of the sensor is too far from the control system then processes the sensor in this induction motor speed measurement results become less accurate. To overcome these problems required an observer to observe the functioning of the torque and current, so that motor speeds can be predicted. Then developed some observer, there

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are that using the SCFNN observer by its application using several methods of training algorithm, for example: Backpropagation (BP), Levenberg-Marquardt (LM) etc.

2. Research Method

The purpose of this study was to compare the initial rotation performance responses of induction motor between observer method SCFNN LM training algorithm that performed by the author with induction motor torque control technique known as the DTC with RNN observer conducted by researchers [8].

The result is expected to be used as guidance in determining the proper choice for method of observation in induction motor speed control. With the right method, can enhance better performance for the system. With the improvement of system performance, is expected to increase work efficiency in the industrial world.

This method of speed vector sensorless for induction motor control was be developed so rapidly in the control system applications, due always must obtained of more accurate results [1-3].

The observer method will be developed using neural network observer so that the simulation results show better performance and flux errors can be maintained with small intervals.

Fuzzy Neural Network (FNN) combines his skills in the handling of fuzzy information and learning on the learning parameters based on back propagation algorithm, the parameters of membership functions related development customized weight and structure of the FNN are determined. Despite this appearance of the structure of FNN control with the ability of online teaching and learning parameters are acceptable, but if the amount of data first collected in front of a lot thus for the implementation plan usually spend a lot of time. [4]

To overcome the problem of achieving fast learning objectives, be developed a Self-Constructing Neural Fuzzy Inference Network (SCNFIN). To demonstrate the phase structure of the learning parameters were simultaneously, network structure with the parameters of both complex learning. therefore SCNFIN difficult to be implemented or applications of practical. [5].

Using the method of Self Contructing Fuzzy Neural Network (SCFNN) by learning to use backpropagation [6] and Levenbewrg-Marquardt [7] to obtain the output according to the given setpoint.[6-7]

Another technique developed by I. Takahashi namely torque control technique of induction motor, known as Direct Torque Control (DTC). With the DTC torque control is possible with a good performance without using a mechanical transducer on the motor shaft. By [8] used DTC with RNN observer.[8].

3. Results and Analysis

The results obtained from this study is a simulation output of that be applied to the model, while the analysis to be used is comparison method

3.1. The Modeling

Developed from several studies that have been done by Seong-Hwan Kim, et al. [1], Iradiratu [3] and Sutedjo [6] the block diagram of the system developed in this research is like Figure 1.

FOC is a method of setting the field on ac motor, where the coupled system is converted into decoupled system. By strengthening the current system and the motor load current can be controlled separately, so torque and flux can also be arranged separately. Block diagram illustrating the basic principle of the system Dcoupled Field Oriented Control (FOC decoupled) induction motor is shown in Figure 2.

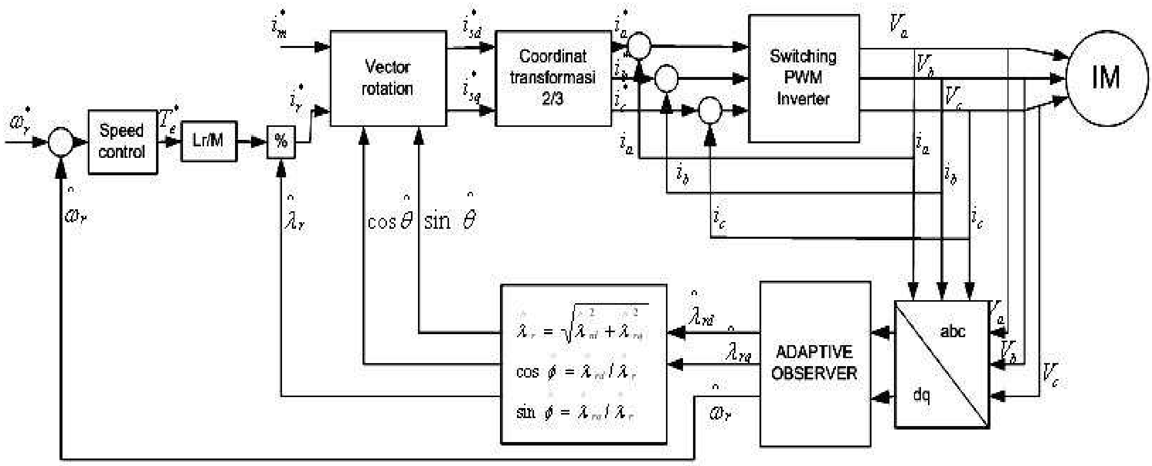

Figure 1. Configuring System Speed-Sensorless Vector Control for Induction Motors with SCFNN

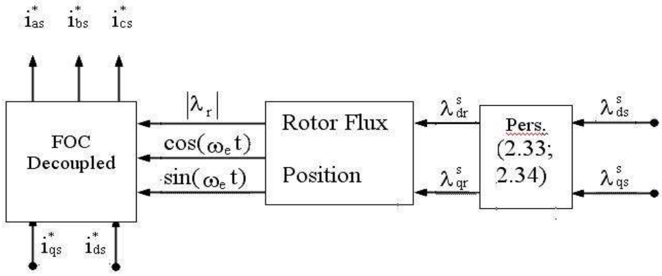

Figure 2. Block diagram of decoupled FOC Induction Motors

Rotation vector of the magnetization current and torque producing current reference phase currents are used for PWM inverter control signal. The resulting voltage inverter will be used by the induction motor stator. PWM inverter model is shown in Figure 3.

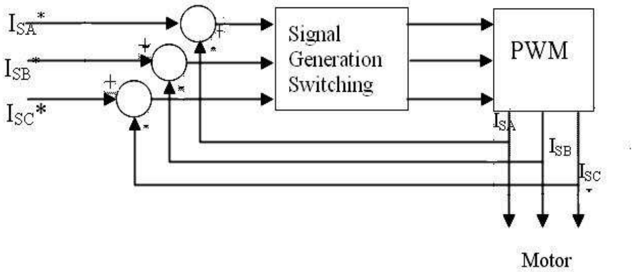

Figure 3. PWM Inverter

The equivalent circuit of induction motor in d-q coordinates can be seen in Figure 4.

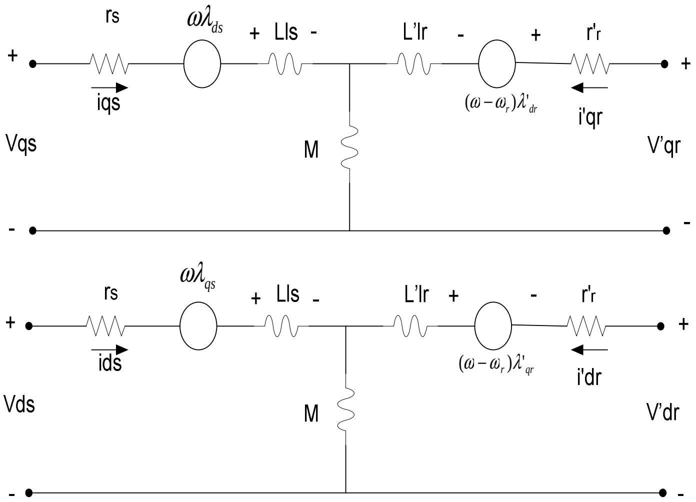

Figure 4. Induction Motor Equivalent circuit in d-q coordinates

The equivalent circuit of induction motor in dq coordinates, by entering the rotor voltage (Vr,, = 0), then obtain the stator voltage magnitude which is a function of stator currents and rotor currents in matrix form, as follows:

$$\begin{bmatrix} v_{ds} \\ v_{qs} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s + pL_s & -\omega_s L_s & pM & -\omega_s M \\ \omega_s L_s & R_s + pL_s & \omega_s M & pM \\ pM & -(\omega_s - \omega_r)M & R_r + pL_r & -(\omega_s - \omega_r)L_r \\ (\omega_s - \omega_r)M & pM & (\omega_s - \omega_r)L_r & R_r + pL_r \end{bmatrix} . \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix} \tag{1}$$

with: p = $\frac{d}{dt}$ If observed at stationary coordinates (ω_s = 0), then equation (1) becomes:

$$\begin{bmatrix} v_{ds} \\ v_{qs} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} R_s + pL_s & 0 & pM & 0 \\ 0 & R_s + pL_s & 0 & pM \\ pM & \omega_r M & R_r + pL_r & \omega_r) L_r \\ -\omega_r M & pM & -\omega_r L_r & R_r + pL_r \end{bmatrix} . \begin{bmatrix} i_{ds} \\ i_{qs} \\ i_{dr} \\ i_{qr} \end{bmatrix} \tag{2}$$

3.2. The Methods

In Self Constructing Fuzzy Neural Network with the Levenberg Marquardt Learning Methode. This controller is a fuzzy controller input, so that input is numeric data in the form of error .. Fuzy basic structure of a neural network as in Figure 5.

In the first layer occurs only process crisp input of data that is error (X1) and Delta errors (X2) to forward the signal to the next layer.

In the second layer occurs fuzyfikasi process and the formation of membership functions. The function used is Gaussian function.

$$u_{A_i^j} = exp\left(\frac{(x_i - m_{ji})^2}{\sigma_{ji}^2}\right) \tag{3}$$

with the M_{JI} and σ_{ji} is the average (mean) and standard deviation.

In the third layer. is the initial condition determination of fuzzy rules. Ledge is to obtain a multiplication result of all the component inputs of the error and the delta error with the equation:

$$u_j = u_{A_1^j}(x_1) u_{A_2^j}(x_2) \cdots u_{A_n^j}(x_n) = \prod_i u_{A_i^j}(x_i) \tag{4}$$

with u_j is an output node rule number-j

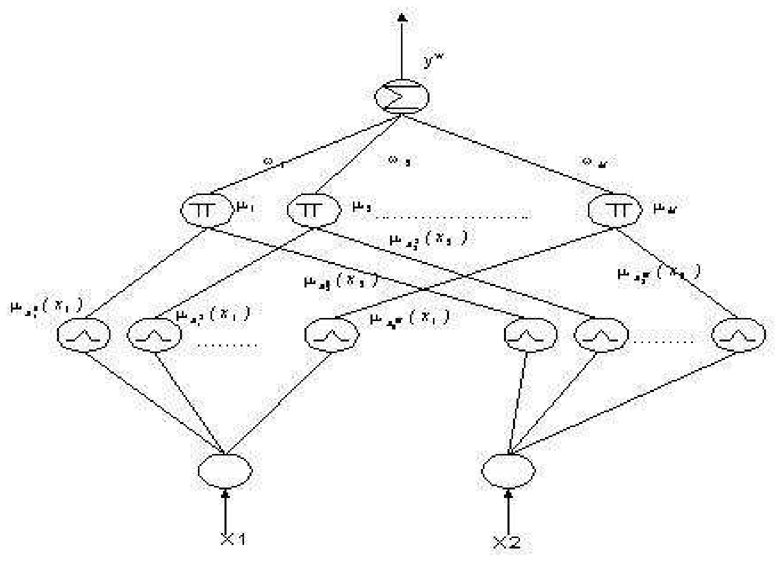

Figure 5. The basic structure of SCFNN

Layer Four: Serves to add up all input signals disimbulkan with Σ, then formulated in the equation was then performed defuzifikasi.

$$y^* = \sum_{j=1}^{M} w_j u_j \tag{5}$$

In SCFNN there are two types of learning algorithm, namely learning the structure and learning parameters. Learning the structure used to seek input space partition of fuzzy logic and fuzzy logic that aims subject: minimizing the number of rules and minimize the fuzzy sets in the universe talks of each variable parameter input.Learning using supervised learning algorithms, whereas to determine the weight and parameters of membership function set with backpropagasi learning algorithms.

The first step in learning the structure is to determine whether or not to do the learning structure. If Emin |≤ e | or Emin Δ |≤ Δ e |. By Emin and Emin Δ is a positive constant, then the learning structure is needed. Next define a new node (membership function) in layer 2 and connecting fuzzy logic rule in layer 3. If there is one cluster is given in the input will cause the existence of a fuzzy logic rule in layer 3, the power equation of ignition (firing strength) of a rule for each input data xi can be shown as a point of where the input data related to the cluster data. Firing strength obtained from (4) which is used as the measurement of angles:

$$D_j = U_J \;\; j = 1,..., Q(t) \tag{6}$$

with Q(t) is the number of existing rules at time t. Criteria for the establishment of a new fuzzy rule for new input data is stated as follows. By determining the maximum angle measurement D_{max}

$$D_{\max} = \max_{1 \le j \le Q(t)} D_j \tag{7}$$

If $D_{max} \le \overline{D}$, then shaped membership function with $D \in (0,1)$. Then the mean and standard deviation of the new membership function declared in advance with a particular value in heuristics or how lain.Jadi the mean, standard deviation of the new membership function as follows:

$$m_i^{(new)} = x_i \tag{8}$$

$$\sigma_i^{(new)} = \sigma_i \tag{9}$$

with x_i is the new input data and i is the standard deviation σ.

To avoid a new membership function the same as that already exist, the similarity between the membership function of the old and new should be examined, namely the assumptions that if there are two fuzzy sets A and B with membership function is

$\mu A(x) = exp\ [- (x - m_1)^2/\sigma_1^2]$ *and* $\mu b\ (x) = exp\ [- (x - m_2)^2/\sigma_2^2]$.

And assume $m_1 \ge m_2$.Kemudian $| A \cap B |$ is calculated

$$|A \cap B| = \frac{1}{2}\frac{h^2(x)\left[m_2 - m_1 + \sqrt{\pi}(\sigma_1 + \sigma_2)\right]}{\sqrt{\pi}(\sigma_1 + \sigma_2)} + \frac{1}{2}\frac{h^2(x)\left[m_2 - m_1 + \sqrt{\pi}(\sigma_1 + \sigma_2)\right]}{\sqrt{\pi}(\sigma_1 + \sigma_2)} + \frac{1}{2}\frac{h^2(x)\left[m_2 - m_1 + \sqrt{\pi}(\sigma_1 + \sigma_2)\right]}{\sqrt{\pi}(\sigma_1 + \sigma_2)} \tag{10}$$

with h(x) = max{o, x}.

$$E(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{\sigma_1\sqrt{\pi} + \sigma_2\sqrt{\pi}|A \cup B|^*} \tag{11}$$

Examination performed on all input variables xi. While the value of the Maximum of E_{max} obtained with :

$$E_{\max} = \max_{1 \le j \le Q(t)} E\left\{u\left(m_1^{(new)}, \sigma_1^{(new)}\right),\quad u\left(m_{j1}, \sigma_{j1}\right)\right\} \tag{12}$$

with $u(m_{j1},\sigma_{J1})$ is a Gaussian membership function with mean m_{j1} and standard deviation σ_{J1}; M (t) is the number of i-th membership function of input variables. If $E_{max} \le F$ with $F \in (0,1)$ is a predetermined value, then use the new membership function and the number of M (t).

$$M(\mathrm{t}+1) = M(\mathrm{t}) + 1 \tag{13}$$

So the establishment of membership function associated with the formation of a new fuzzy rule and weighting ω(new).

SCFNN learning algorithm is to determine the parameters of the adaptive rule to adjust the network parameters, based on input-output pairs. If the network parameter vector consists of parameters, then the learning process taking into account the vector of determination of the energy function. This method is generally based learning backpropagasi rule because the gradient vector is calculated in a direction opposite to the output of each node, to explain the learning algorithm parameters SCFNN supervised gradient decent method. Assume the energy function E is defined as:

$$E = \frac{1}{2}(\omega_m - \omega_r)^2 = \frac{1}{2}e_m^2 \tag{14}$$

Then the parameter learning algorithm based on backpropagasi described as follows:
Layer 4: The error dipropagasi calculated as:

$$\delta^4 = -\frac{\partial E}{\partial y^*} = \left[-\frac{\partial E}{\partial e_m}\frac{\partial e_m}{\partial y^*}\right] = \left[-\frac{\partial E}{\partial e_m}\frac{\partial e_m}{\partial \omega_r}\frac{\partial \omega_r}{\partial y^*}\right] \tag{15}$$

and the weighting is updated magnitude

$$\Delta\omega_j = -\eta_\omega \frac{\partial E}{\partial \omega_j} = \left[-\eta_\omega \frac{\partial E}{\partial y^*}\right]\left(\frac{\partial y^*}{\partial \omega_j}\right) = -\eta_\omega \delta^4 u_j \tag{16}$$

by a factor is the learning-rate parameter of the weighting. Weighting in layer 4 was updated:

$$\omega_j(N+1) = \omega_j(N) + \Delta\omega_j \tag{17}$$

with N the number of iterations of the j-th
Layer 3: In this layer only the error that needs to be calculated and dipropagasi:

$$\delta_j^3 = -\frac{\partial E}{\partial u_j} = \left[-\frac{\partial E}{\partial y^*}\right] * \left[\frac{\partial y^*}{\partial u_j}\right] = \delta^4 \omega_j \tag{18}$$

Layer 2: Error is calculated as follows:

$$\delta_{ji}^2 = -\frac{\partial E}{\partial u_{A_i^j}} = \left[-\frac{\partial E}{\partial y^*}\frac{\partial y^*}{\partial u_j}\right]\left[\frac{\partial u_j}{\partial u_{A_i^j}}\right] = \delta_j^3 \tag{19}$$

rule of update of m_{ji} is :

$$\Delta m_{ji} = -\eta_m \frac{\partial E}{\partial m_{ji}} = \left[-\eta_m \frac{\partial E}{\partial u_{A_i^j}}\frac{\partial u_{A_i^j}}{\partial m_{ji}}\right] = \eta_m \delta_{ji}^2 \frac{2(x_i^2 - m_{ji})}{(\sigma_{ji})^2} \tag{20}$$

And rule of updates of σ_{ji} *is :*

$$\Delta\sigma_{ji} = -\eta_\sigma \frac{\partial E}{\partial \sigma_{ji}} = \left[-\eta_\sigma \frac{\partial E}{\partial u_{A_i^j}}\frac{\partial u_{A_i^j}}{\partial \sigma_{ji}}\right] = \eta_\sigma \delta_{ji}^2 \frac{2(x_i^2 - m_{ji})}{(\sigma_{ji})^2} \tag{21}$$

with η_m and η_σ are the learning-rate parameter of the mean and standard devisasi Gaussian function. Mean and standard deviation of the membership function in this layer is updated by:

$$m_{ji}(N+1) = m_{ji}(N) + \Delta m_{ji} \quad (22)$$

$$\sigma_{ji}(N+1) = \sigma_{ji}(N) + \Delta\sigma_{ji}) \quad (23)$$

Having obtained equation this equation then simulated a series of controls with Self Constructing Neural Fuzzy Networks with induction motor plant.

In this study the training methods Backpropagasi studied by [5] is replaced with Levenberg-Merquard training (LM). LM training methods are a combination of Newton with the Steepest Descent algorithm. When the Gradient Descent method is expressed as equation:

$$W_{kj}(t+1) = W_{kj}(t) + \alpha.\delta_k.Z_j \quad (24)$$

The equation above can be simplified to

$$W_{k+1} = W_k + \alpha.g \quad (25)$$

Where g is the gradient vector. And the Newthon equation is:

$$W_{k+1} = W_k - A_k^{-1}.g \quad (26)$$

A_k is the Hessian matrix (its elements are the second derivative of the weighing error) following

$$A = \begin{bmatrix} \frac{\partial^2 E}{\partial W_1^2} & \frac{\partial^2 E}{\partial W_1 \partial W_1} & .... & .... & \frac{\partial^2 E}{\partial W_n \partial W_1} \\ \frac{\partial^2 E}{\partial W_1 \partial W_2} & \frac{\partial^2 E}{\partial W \partial W_2^2} & .... & .... & \frac{\partial^2 E}{\partial W_n \partial W_2} \\ .... & .... & .... & .... & .... \\ .... & .... & .... & .... & .... \\ \frac{\partial^2 E}{\partial W_1 \partial W_n} & \frac{\partial^2 E}{\partial W_2 \partial W_n} & .... & .... & \frac{\partial^2 E}{\partial W \partial W_{2n}^2} \end{bmatrix} \quad (27)$$

"A" can be written as:

$$A = 2J^T J \quad (28)$$

where: J is the Jacobian matrix

Equation improvement weighing of LM training methods are:

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k^T e \quad (29)$$

If the value of $\mu = 0$, then the LM training methods will be identical to the method of Gauss Newthon, is not μ, it when the LM training method will be equal to Backpropagasi (steepest descent).

Having obtained the equation, this equation it can be simulated to a control circuit with SCFNN LM training methods with induction motor plant.

3.3. The Simulations

Block diagram of induction motor speed control system without speed sensor of Figure 1, And on the adaptive observer using self contructing fuzzy neural network, as shown in Figure 6 and Figure 7.

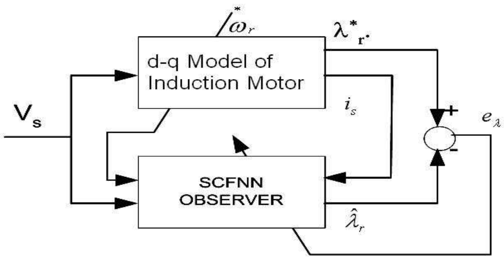

Figure 6. Structure of flux estimates

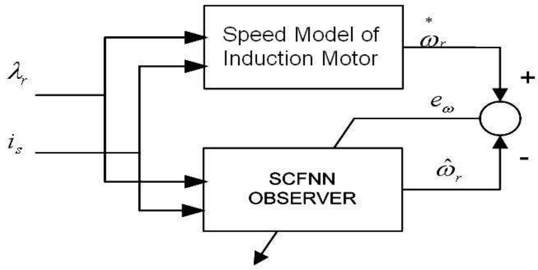

Figure 7. Speed Estimation Structure

Figure 6, the structure of estimation to obtain estimates of flux, each of which consists of direct flux λ_{dr} and quadratur flux λ_{qr}, the results of these two parameters are used to input the speed estimation, shown in Figure 7. The induction motor parameters for SCFNN learning data used in obtaining the target goals as follows:

- Direct flux C, consist of I_{ds}, V_{ds}, V_{qs}, ω_r,
- Quadratur flux λ_{dr}, consists of I_{qs}, V_{qs}, V_{qs} ω_r,
- Speed ω_r consists, λ_{dr}, λ_{qr} I_{ds}, and I_{qs}.

The Learning methods to estimate the flux identification of induction motor speed using a self-constructing fuzzy neural network where the network consists of four layers, namely the input of 4, linguistic, precondition and 1 output. Linguistic, precondition and output to gain value of λ_{dr}, λ_{qr} and ω_r. The learning process uses 4 neurons.

Inputs ie Vs, Is, and λ_r, learning done as much as 5 epoch. If learning outcomes have not convergent or not on target there will be additional new membership function, the addition stops when a convergent learning outcomes .. The starting price is determined weighting between 0 and 1 to find the optimal parameters that produce the best performance.

In the process of estimation there are three SCFNN to complete the estimated direct flux λ_{dr}, flux quadratur λ_{qr}, after completion of this process there is a complete SCFNN speed estimation ω_r. Off-Line Learning self-constructing fuzzy neural network observer for identification of direct flux λ_{dr}, shown in Figure 8.

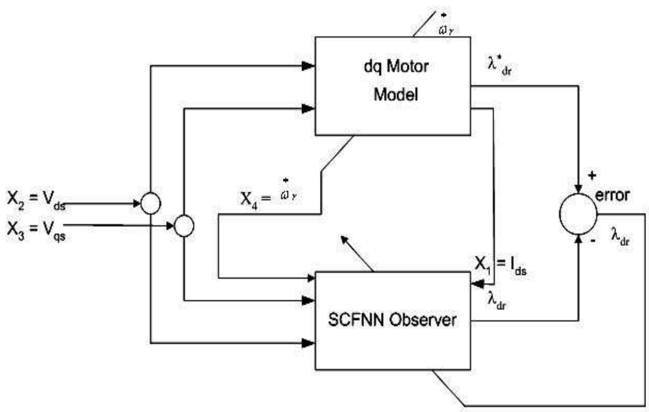

Figure 8. Estimation structure of Direct Flux λ_{dr} Using SCFNNO

Figure 8, illustrates the structure of direct flux estimator λ_{dr} using SCFNN, and the input consists of I_{ds}, V_{ds}, V_{qs} and ω_r, in enter into the block SCFNNO.

In the motor model block, determine the value of velocity (speed reference $\overset{*}{\omega_r}$) to obtain a direct reference flux λ * dr. For the direct flux SCFNNO produce learning $\hat{\lambda}_{dr}$, reference and learning the difference between the value obtained error or direct flux estimation.

The output from SCFNNO flux is defined as direct learning $\hat{\lambda}_{dr}$, which is then used as inputs that can be changed. If the estimated direct flux is the deviation of actual direct flux and error models of the relationship between the flux of direct flux learning $\hat{\lambda}_{dr}$ and flux direct reference λ * dr. So the error is the backpropagation of SCFNN and the imposition of SCFNN is adjusted on line to reduce the error. Finally, the output of SCFNN an actual direct flux model.

Figure 9, illustrates the structure of SCFNN SCFNNO to get the results that follow the actual speed.

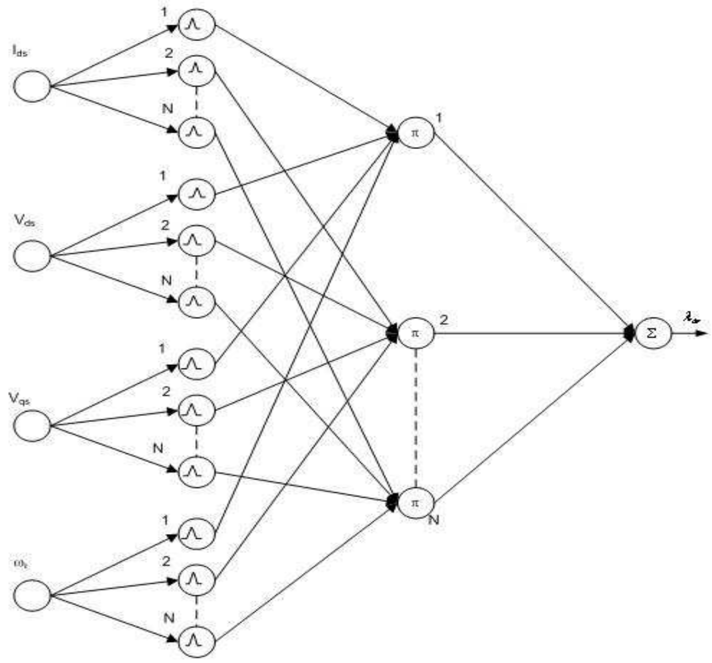

Figure 9. Internal Structure SCFNNO

There are 3 blocks of SCFNNO, namely SCFNNO blocks for, λ_{dr}, λ_{qr} and ω_r, SCFNNO block for λ_{dr} and λ_{qr} : counted first, then the results incorporated into the SCFNNO block. ω_r

At the time of learning, the number of rules created for each input can be different from the rule that is created for a block SCFNNO, because the characteristics of I_{ds}, I_{qs}, V_{ds}, V_{qs}, and ω_r are not the same.

The data of induction motor used for simulation are:

Rs = stator resistance (ohms) = 176
Rr = rotor resistance (ohms) = 190
The number of pairs of poles = 2
Ls = stator inductance (H) = 3.79
Lr = rotor inductance (H) = 3:31
M = inductance coupled (H) = 3:21
Kd = constant friction (Kg.m2 / s) = 1.9e-5
Voltage = 115 V Frequency = 60 Hz

and Figure 10 is the current speed Motor Response Speed Reference Start with 750 rad / sec using LM training SCFNNO [8] and Figure 11. Mechanical Control DTC with RNN conducted by researchers [7]

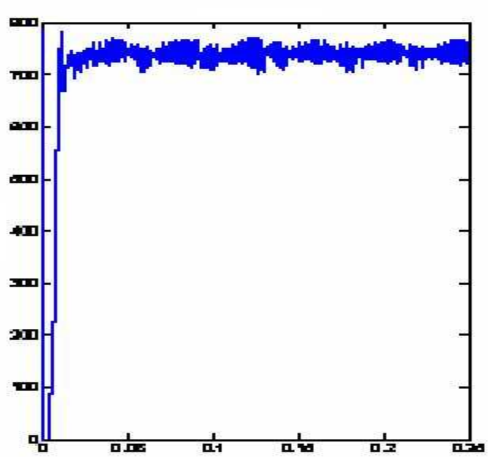

Figure 10. Initial round of motor responses with reference speed 750 rad / sec Observer LM

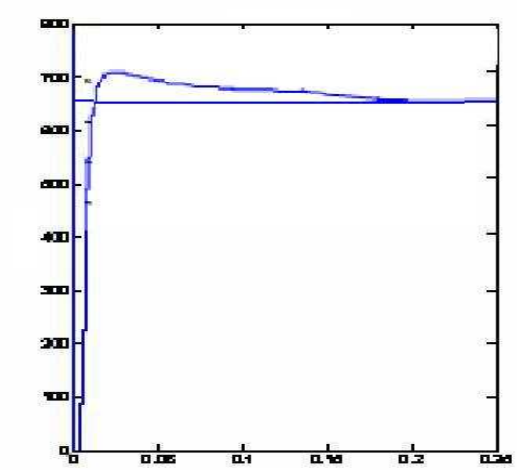

Figure 11. Motor speed response at the Speed Reference Start with 750 rad / sec with RNN observer and for a more accurate figure can be seen in the following table 1.

Table 1 Comparison of performance of Early Motor Speed Response Between LM Observer and RNN Observer with a speed of 750 rpm Reference

No	Performance	RNN Observer	LM Observer
1.	Peak (rad/sec)	810	790
2.	Rise Time (sec)	0.0125	0.008
3.	Settling Time (sec)	0.364	0.025
4.	Peak Time (sec)	0.045	0.0125
5.	Overshoot (%)	7.99990	5.33333

Where a longer rise time means lower capacitive feedthrough, and thus lower coupling noise, and in the table shows that the rise time with FNN method is longer than the LM method, that means the FNN method produces a rise time better than the LM

Settling time is the time required for an output to reach and Remain within agiven error band following some input stimulus, are in the table above showsthat the RNN method has a longer settling time than the LM method, which it means the achievement of steady state methods LM is faster, it is because the error of the selected band is still too large, but along with the error bandsare increasingly reduced, the RNN method would be better, that is, when will be applied on systems that require high precision

Although the peak and the overshoot for the LM method a little better than RNN method, but the peak time is much better method of RNN, so overall, particularly for systems that require high precision, RNN methodcan be said to be better

4. Conclusion

On start motor with a par round of 750 rad / sec on RNN observer happens overshoot is 7.9999% 5.3333% LM, RNN peak at 810 rad / sec is the LM 790 rad / sec, rise time RNN = 0.0125 sec are LM 0008 seconds, settling time RNN = 0.364 is LM = 0025. By comparing the simulation results of both observe methods can conclude that parameters of overshoot, rise time, settling time, peak time and peak at observer LM is better than RNN. From the results of this research is expected to be reference in determining the choice of appropriate methods of observation in induction motor speed control. With the right method, can enhance better performance of the system. With the improvement of system performance, is expected to increase work efficiency in the industrial world.

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